Applications of Deep Learning in GIS – Spatiotemporal data mining and forecasting

Thesis Presentation

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Contribution

- In ECE), I compared as many models as I could.
  - DEEPFORECAST multi-LSTM is the best
    - 1.575 RMSE, 1.159 MAE
  - Among competing models, more complex ones aren't always better.
    - Proven by metrics to be shown
  - PEMS-BAY trained STDL models better than METR-LA.
- In my CEHE,
  - I chose familiar models of each domain (S/T) to train with my fire event dataset
  - VAE is the best in the space domain
    - 1.14178919 RMSE, 0.37329638 MAE
  - FBProphet is the best in the time domain
    - 6.97231 RMSE, 5.045342 MAE
  - LSTM doesn't always beat FBProphet

Motivation

Intelligent transport system (ITS)

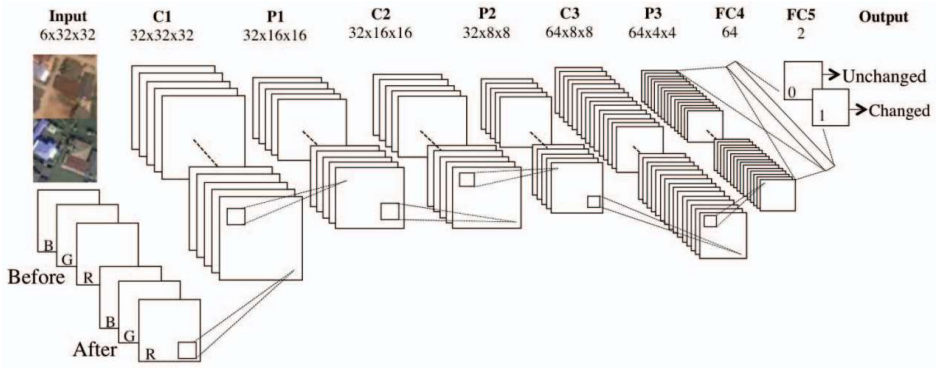
Disaster & Weather forecast

To study DL-Implementations in STDM

To mine ST-data is laborious

- Deep learning can help -> self-feature extraction

Do newer STDM-DL models outperform older ones?

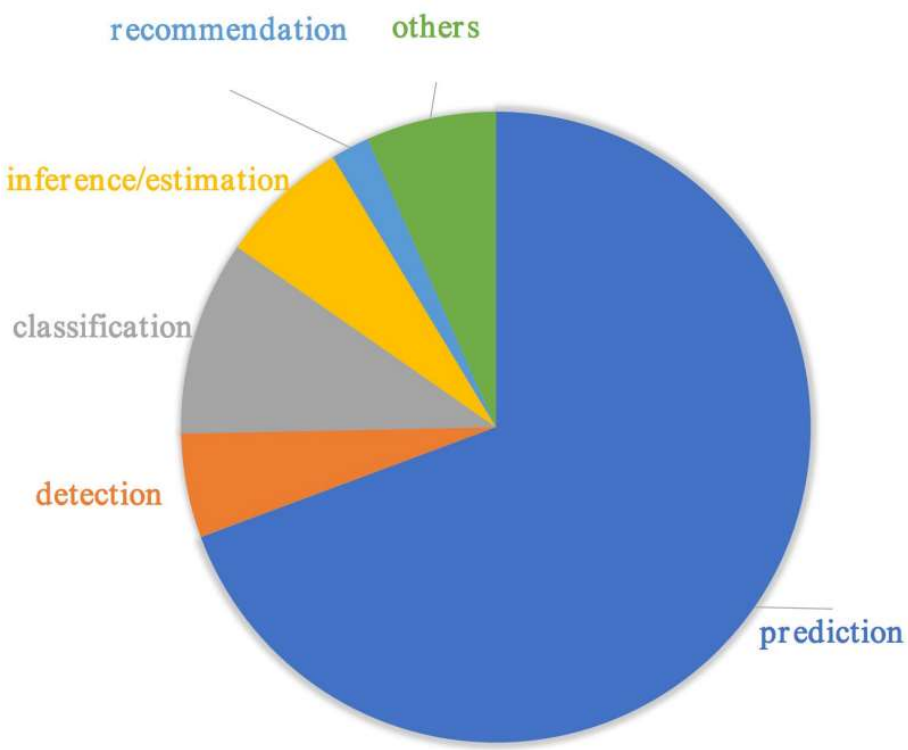


Uses of STDM

- Meteorology
- Transportation (Most popular)
  - ITS
- On-Demand Services
  - Taxi-hailing apps
- LBSN
- Criminology
- Etc.

Literature Review - Early WORKS

- Disaster Impact Analysis & Detection
  - Doshi et al.'s CNN [1,2]
  - Amit & Aoki FC-CNN [3]
  - Fang's LSS-LSTM [6]
- GEO-Feature Detection
  - Iglovikov et al.'s UNET [4]
- Earlier surveys
  - Wang et al. [8]
  - Atluri et al. [19]



Literature Review – Implemented models

2.2 (ECE)

- DCRNN [7]
- STGCN [9]
- ST-METANET[16]
- CRANN [15]
- Adaptive GCNN [71]
- Attention-based ST-GCN [72]
- Deepforecast Multi-LSTM[73]
- Spacetimeformer [80]

2.3 (CEHE)

- Autoencoders
  - BAE
  - VAE
  - CVAE
- GAN
  - DCGAN
  - WGAN
  - LSGAN
- FBProphet
- ARIMA
- LSTM
  - MMS = Min Max Scaling
    - Pre: done before TTS
    - Post: done after TTS

Hypothesis

- Q1: STDM DL-models can do a variety of learning and predictions, but how well can they do?
  - Metrics: MSE, RMSE, & MAE
- Q2: If I have a custom dataset with its data structure visualised, which model to be learned from it?
  - Such as the “NTPC-fire_2015-17” dataset
    - Which is small.
  - What if I vary some hyperparameters?

Experiment Episode 1: Exploratory Comparative Experiment (ECE)

- Hyperparameters: default
- Optimiser: Adam
- Environment: COLAB GPU, TWCC
- Method: run models, record and compare their metrics.

Architecture	Architecture Description	Dataset Name/Desc	learning rate	Epochs	Major DL Module
Taxi-Simple-LSTM-Pytorch	Simple-LSTM	Time series of Taxi-Uber DS. (2014-15)	0.01	2000	Pytorch
Uber-Simple-LSTM-Pytorch	Simple-LSTM	Time series of Taxi-Uber DS. (2014-15)	0.01	2000	Pytorch
Taxi-Simple-LSTM-Keras	Simple-LSTM	Time series of Taxi-Uber DS. (2014-16)	0.001	100	TensorFlow Keras
Uber-Simple-LSTM-Keras	Simple-LSTM	Time series of Taxi-Uber DS. (2014-17)	0.001	100	TensorFlow Keras
CRANN-Temporal	Bahdanau Att.Mech Autoencoder (LSTM based)	temporal time series of hourly/daily car traffic (in Madrid)	0.01	200	Pytorch
CRANN-Spatial	CNN+ST-Att.Mech	graph data captured by 30 sensors + Timestamps (A 17000x30 matrix)	0.01	200	Pytorch
CRANN-Dense	Fully Connected Feedforward NN (FCFFNN)	dense 3D+ tensor of both preceding modules	0.01	200	Pytorch
Seq2seq (flow)	Improved Seq2eq	Beijing TDrive	0.01	200	MXNET
GAT Seq2seq (flow)	Improved Seq2eq	Beijing TDrive	0.01	200	MXNET
ST-Metanet (flow)	Improved Seq2eq	Beijing TDrive	0.01	200	MXNET
Seq2seq (speed)	Improved Seq2eq	METR-LA	0.01	200	MXNET
GAT Seq2seq (speed)	Improved Seq2eq	METR-LA	0.01	200	MXNET
ST-Metanet (speed)	Improved Seq2eq	METR-LA	0.01	200	MXNET
AGCRN	Attentive Graph CRN	Caltrans PEMS04&08	0.003	100	Pytorch
ASTGCN	Attention Based GCN	Caltrans PEMS04&08	0.001	80	Pytorch
Deepforecast	Multi-LSTM	MS_winds - Wind Speed & Flow Dataset	0.001	80	TensorFlow Keras
DCRNN	R-CNN	PEMS & METR-LA	0.001	100	TensorFlow Keras
STGCN	Graph-CNN	PEMS & METR-LA	0.001	50	Pytorch
Spacetimeformer	Transformer opted for ST-data	METR-LA	0.001	80	Pytorch

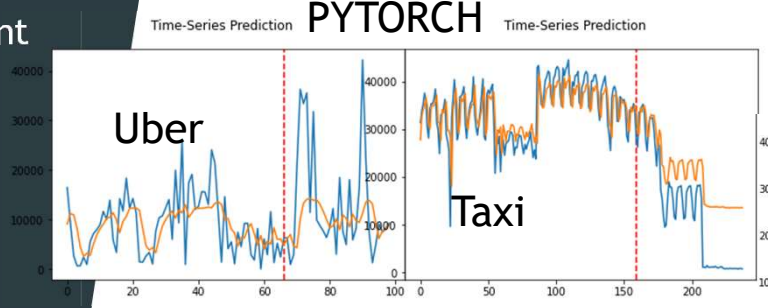
ECE results:

- Deepforecast Multi-LSTM
  - Is the best model to date
  - 1.575 RMSE, 1.159 MAE
- All model performed well
  - At least for their arch.
- LSTM on the TAXI-Uber data
  - Had a poor metrics
  - Simplicity, overfitting, gradient vanishing & explosion

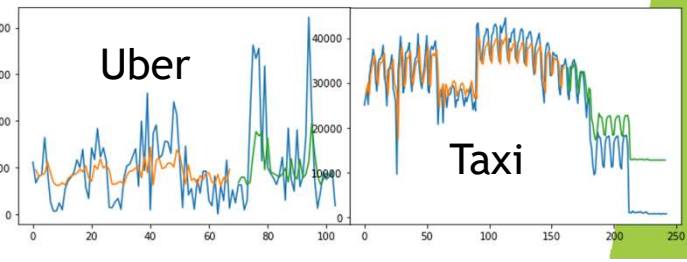
		Key Metrics		Other Metrics	
Architecture	MSE	RMSE	MAE	Type	Value
Taxi-Simple-LSTM-pytorch	72269860	8501.168	5753.569		
Uber-Simple-LSTM-pytorch	0.0332864	0.1824457	0.13018544		
Taxi-Simple-LSTM-Keras	93431556	9666	92.484945		
Uber-Simple-LSTM-Keras	105050200.4	10249.4	83.21		
CRANN-Temporal	6653.6636	81.569992	50.3727684	Bias	-3.82883501
				Relative error %	24.85518008
CRANN-Spatial	55740.719	236.09472	117.7406616	Bias	-14.2317371
				Relative error %	9.053748846
CRANN-Dense	67264.055	259.35315	138.2879333	Bias	-4.71734381
				Relative error %	24.85518008
Seq2seq (flow) [14]	1626.986623	40.33592224	21.3		
GAT Seq2seq (flow) [14]	1098.041371	33.13670731	18.3		
ST-Metanet (flow) [14]	813.1885148	28.51646042	16.9		
Seq2seq (speed) [14]	44.4751941	6.668972492	3.55		
GAT Seq2seq (speed) [14]	36.92343427	6.076465607	3.28		
ST-Metanet (speed) [14]	33.63158961	5.799274921	3.05		

		Key Metrics		Other Metrics	
Architecture	MSE	RMSE	MAE	Type	Value
AGCRN - PeMSD4	1040.761367	32.26083333	19.69416667	MAPE (TWCC)	13.02040833
AGCRN - PeMSD8	718.9101563	26.8125	17.01583333	MAPE(COLAB)	10.65138333
ASTGCN - PeMSD4	1173.7476	34.26	21.84	MAPE	0.15
ASTGCN - PeMSD8	809.4025	28.45	18.5	MAPE	0.11
Deepforecast	2.481881285	1.5753988	1.1590073	NRMSE_maxmin (%)	15.575216
				NRMSE_mean(%)	43.097104
DCRNN(Metr-LA)-STA - 15min	75.5161	8.69	4.02	MAPE	9.39
DCRNN(Metr-LA)-STA - 1hr	201.9241	14.21	6.79	MAPE	16.71
DCRNN(Metr-LA)-VAR- 15min	60.5284	7.78	4.37	MAPE	10.08
DCRNN(Metr-LA)-VAR - 1hr	114.0624	10.68	6.5	MAPE	15.84
DCRNN(Pemsbay)-STA - 15min	11.7649	3.43	1.6	MAPE	3.24
DCRNN(Pemsbay)-STA - 1hrmin	49.2804	7.02	3.05	MAPE	6.84
DCRNN(Pemsbay)-VAR - 15min	9.5481	3.09	1.74	MAPE	3.59
DCRNN(Pemsbay)-VAR - 1hr	26.1121	5.11	2.92	MAPE	6.46
STGCN - 15min	16.532356	4.066	2.231	%Wmape	5.206
STGCN - 30 min	33.051001	5.749	3.04	%Wmape	7.386
STGCN - 45min	46.744569	6.837	3.623	%Wmape	8.927
Spacetimeformer [80]	36.21	6.017474553	2.82	MAPE	7.71
				model.loss	0.258

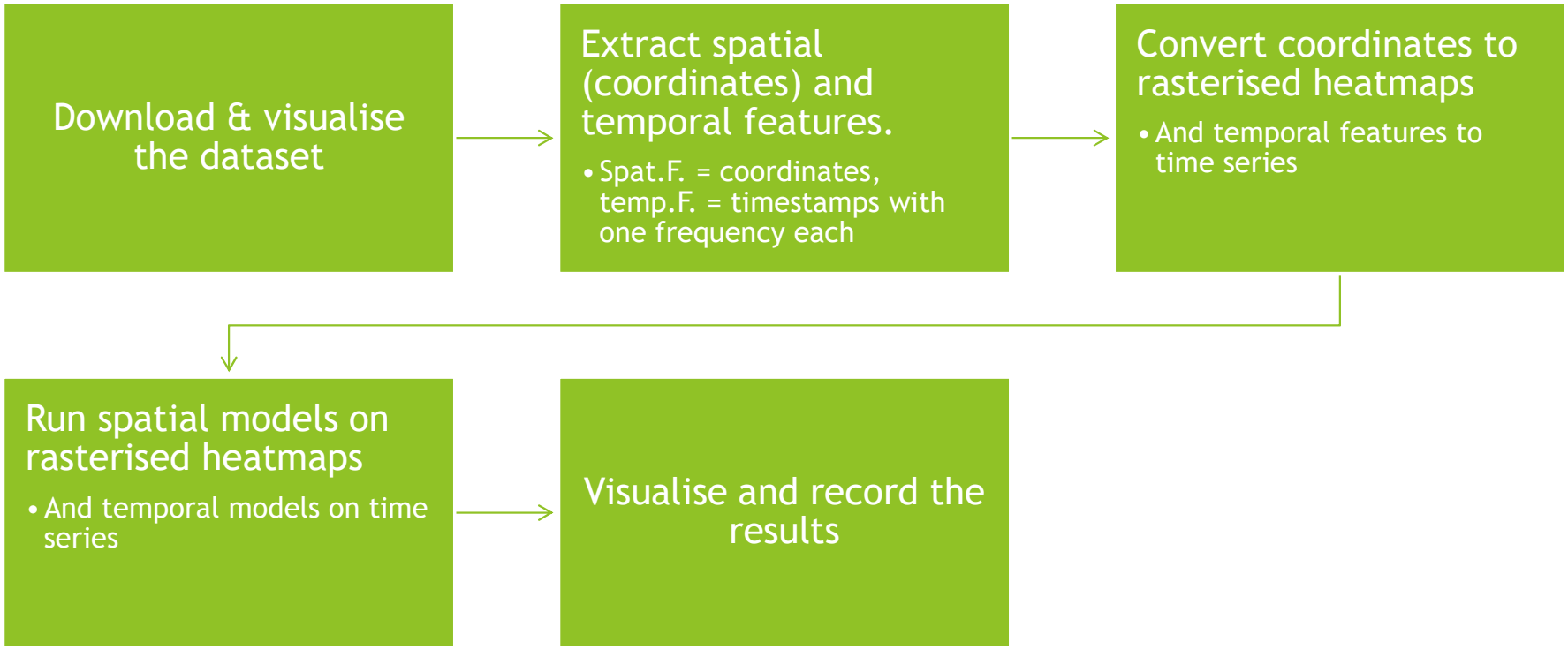
PYTORCH



TF-Keras



CEHE – Procedure



EP2: Custom Event Heatmap Experiment (CEHE)
Hyperparameters (HPs):
- Epochs: 100
- Optimiser: Adam, LR = 0.001
- OTHERWISE, default.

- *In the spatial domain*
- *VAE is the Best*
  - *Due to moderate simplicity* & well tuned HPs despite minimal touches
- Due to my small data size (36samples, 36*784 rpsns)
  - S-Ms are noticeably better than T-Ms
  - (GANs vs AEs)
- *In the temporal domain (1096 samples)*
- *FBProphet is the best*
  - *Never overfits but can be overtaken by PreMMS LSTM if well tuned.*
- *Hidden subtest:*
  - *Add lookback steps (+)*
  - *Add more LSTM cells (+)*

MODEL	DOMAIN	Batch size / freq	Train Metrics:				Test Metrics:			
			MSE	RMSE	MAE	MAPE	MSE	RMSE	MAE	MAPE
Pre-MMS-LSTM4	Time		91.769263	9.579627	5.283182	0.248342	52.195229	7.224627	5.508191	0.37734
Post-MMS-LSTM4-noLB	Time	1day +1day-lookback	7.679134	2.771125	1.556069	0.133908	61.438013	7.83824	5.954068	0.29369
Post-MMS-LSTM-LB5	Time	1day +5day-lookback	7.582465	2.753628	1.559106	0.138684	57.692435	7.595554	5.70559	0.283949
BAE	Space	24 train / 12 test / 9 show	4.636669	2.153292 7	1.8429354	1541306600	5.944328	2.438099 1	2.1663473	1860365700
DCGAN	Space	12	8.476757	2.911487 09	0.8005478 4	38606776	7.666449 5	2.768835 41	0.7418378	38433640
Fbprophet (37 days)	Time	1 day	n/a	n/a	n/a	n/a	48.613108	6.97231	5.045342	0.281977
CVAE	Space	9	7.666290 8	2.768806 5	0.3827354	177096430	6.733639 2	2.594925 6	0.3442523	174446380
VAE	Space	9	1.303682 6	1.141789 19	0.3732963 8	4.11115E+14	1.085725 5	1.041981 55	0.3522904	4.2458E+14
WGAN-GP	Space	9	12.200706 5	3.492950 97	0.8706569	8.83334E+12	10.96560 1	3.311434 88	0.8160268 7	8.84299E+12
Weekly ARIMA	Time	7 days	n/a	n/a	n/a	n/a	1436.900 57	37.90647 14	28.427122 96	0.195063926
LSGAN	Space	12	197.7799 5	14.06342 61	7.245772	2.64E+16	194.7464 9	13.95516	7.1890564	2.63E+16
Post-MMS-LSTM-Weekly	Time	7 days	227.3708 64	15.07882 2	10.250484	0.086445	852.3835 45	29.19560 8	21.007481	0.143819
Post-MMS-LSTM9	Time	1day +5day-lookback	7.578619	2.752929	1.563434	0.139068	55.893509	5.60772	5.70559	0.281344

PreMMS-LSTM

```
#Form dataset matrix
def create_dataset(df, previous=1):
    dataX, dataY = [], []
    for i in range(len(df)-previous-1):
        a = df[i:(i+previous), 0]
        dataX.append(a)
        dataY.append(df[i + previous, 0])
    return np.array(dataX), np.array(dataY)

#tensor manipulation
tseries = dftempday['freq'].to_numpy()
dftensor=pd.DataFrame(tseries) #forward dataframe
dftensor=np.array(dftensor).astype('float32') #convert to tensor

#[PRE-MMS] normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dftensor)

# split into train and test sets
#here, you can change the test size to make future prediction
train_size = int(len(dataset) * 0.67)
test_size = len(dataset) - train_size
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]

# reshape into X=t and Y=t+1
look_back = 1
trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)
lookback = look_back

# reshape input to be [samples, time steps, features]
trainX = numpy.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = numpy.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
```

PostMMS-LSTM

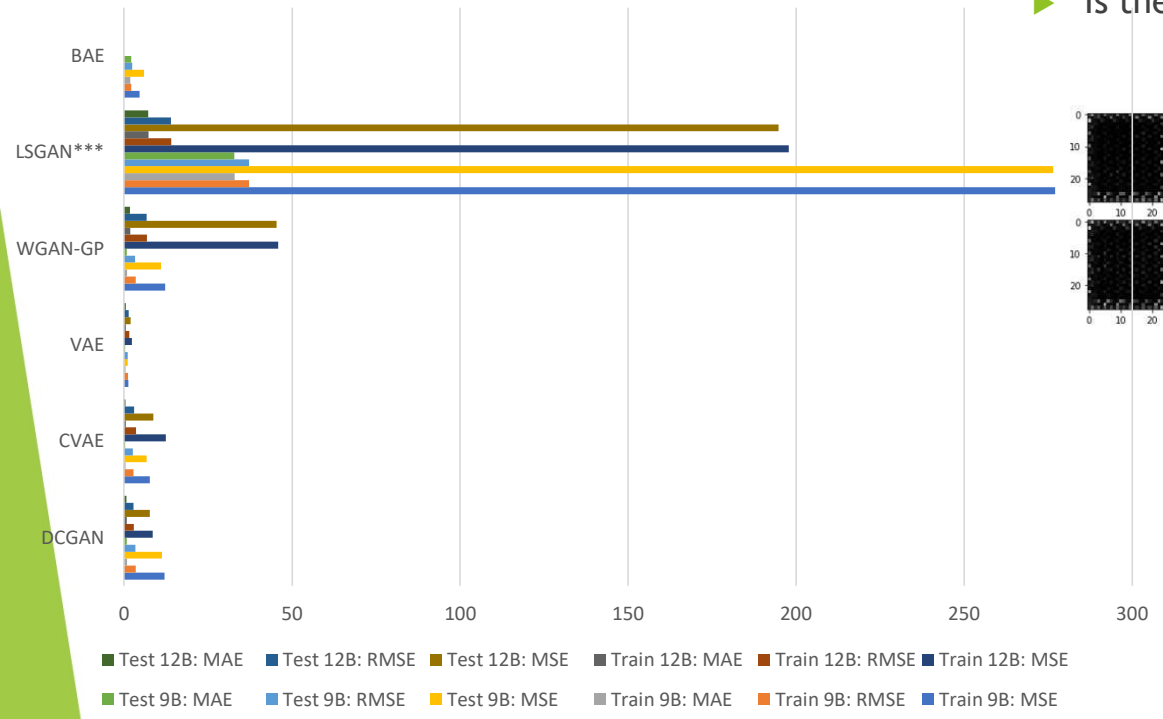
```
#Form dataset matrix
def create_dataset(df, previous=1):
    dataX, dataY = [], []
    for i in range(len(df)-previous-1):
        a = df[i:(i+previous), 0]
        dataX.append(a)
        dataY.append(df[i + previous, 0])
    return np.array(dataX), np.array(dataY)

#tensor manipulation
tseries = dftempday['freq'].to_numpy()
dftensor=pd.DataFrame(tseries) #forward dataframe
dftensor=np.array(dftensor).astype('float32') #convert to tensor

#train-test split
train_size = int(len(dftensor) * 0.8)
test_size = len(dftensor) - train_size
train, test = dftensor[0:train_size,:], dftensor[train_size:len(dftensor),:]

#[POST-MMS] minmaxscaler
scaler = MinMaxScaler(feature_range=(0, 1))
train = scaler.fit_transform(train)
test = scaler.fit_transform(test)

# Lookback period
lookback = 5
trainX, trainY = create_dataset(train, lookback)
testX, testY = create_dataset(test, lookback)

# reshape input to be [samples, time steps, features]
trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
```

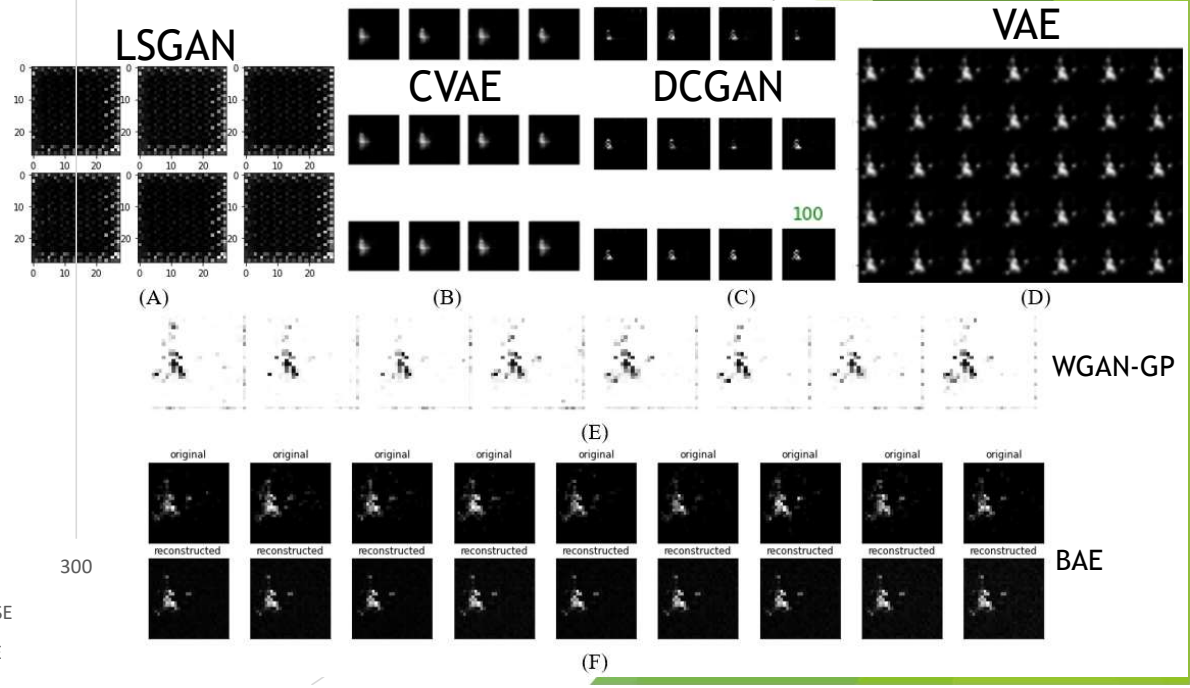
Spatial domain analysis :The Batch Size test

- Expand the training batch (9 -> 12)
  - Improved the DCGAN & LSGAN
  - Worsened other models
  - BAE did not enter the contest
- VAE
  - Is the best spatial model

		DCGAN	CVAE	VAE	WGAN-GP	LSGAN***	BAE
Train 9B:	MSE	12.011371	7.6662908	1.3036826	12.2007065	1385.0496	4.636669
	RMSE	3.46574244	2.7688065	1.14178919	3.49295097	37.21625398	2.1532927
	MAE	0.8862971	0.3827354	0.37329638	0.8706569	32.86514	1.8429354
Test 9B:	MSE	11.25666	6.7336392	1.0857255	10.965601	1382.266	5.944328
	RMSE	3.3550947	2.5949256	1.04198155	3.31143488	37.17883795	2.4380991
	MAE	0.8440172	0.3442523	0.3522904	0.81602687	32.839905	2.1663473
Train 12B:	MSE	8.476757	12.374425	2.326788	45.895508	197.77995	
	RMSE	2.91148709	3.5177302	1.52538125	6.77462234	14.06342608	
	MAE	0.80054784	0.48861146	0.5209149	1.813967	7.245772	
Test 12B:	MSE	7.6664495	8.672948	1.9275316	45.41533	194.74649	
	RMSE	2.76883541	2.9449868	1.38835572	6.73908963	13.95515999	
	MAE	0.7418378	0.41251573	0.48643875	1.7555918	7.1890564	

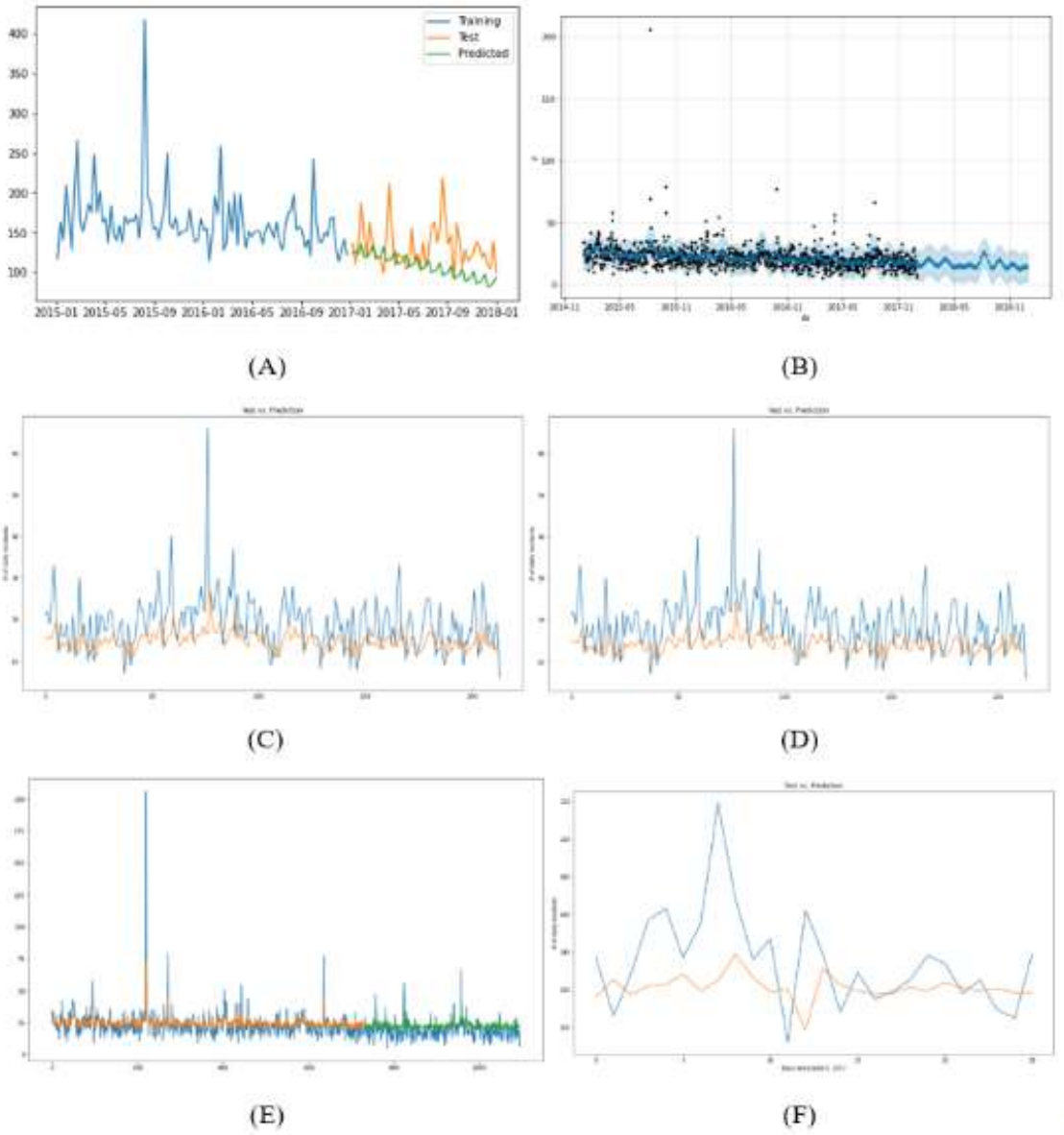
***MSE of the 9B-LSGAN is 5 times higher that it appears





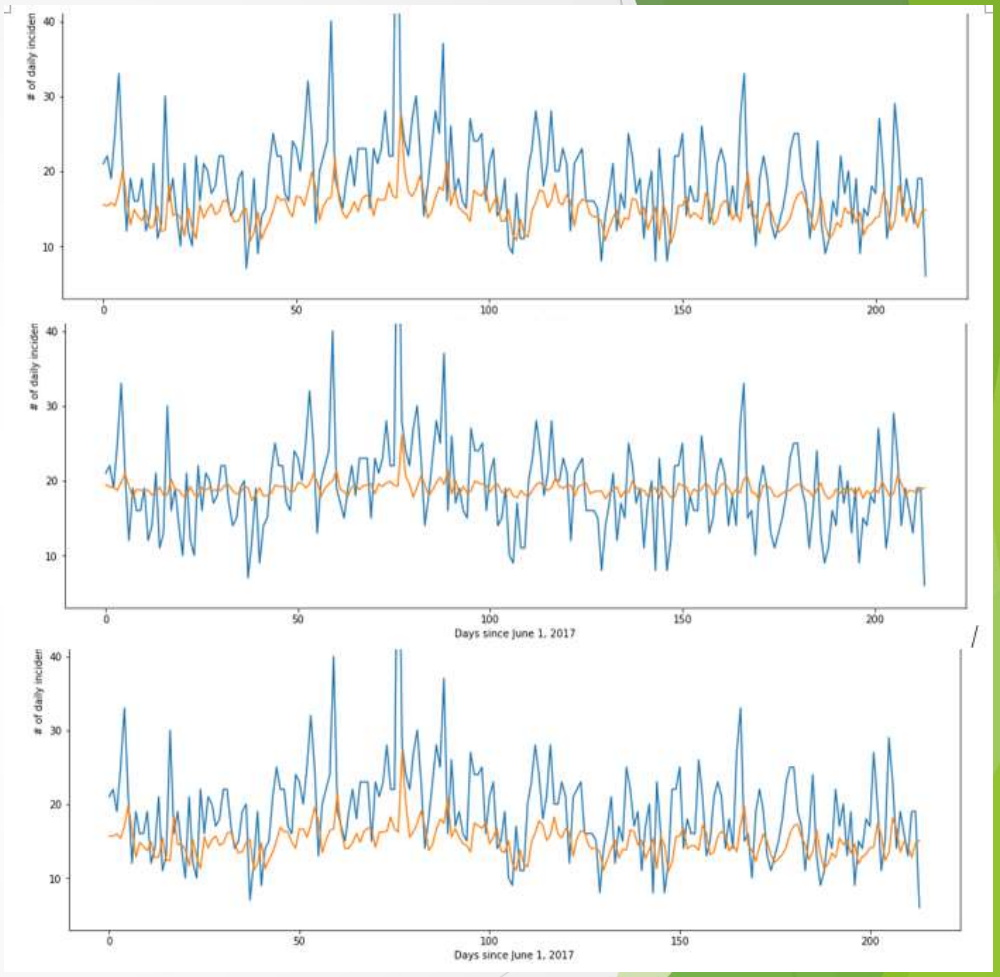
Visualised Frequency Prediction

- A = Weekly Auto ARIMA
- B = FBProphet
- C = PostMMS-LSTM-5LB
- D = PostMMS-LSTM-noLB
- E = PreMMS LSTM
- F = PostLSTM-Weekly



What if I use the weekly model to test the daily data

- Top = LSTM4
- Middle = LSTM4 trained with weekly series
- Bottom = LSTM9



Findings of my Thesis & Discussion (1/2)

- The ECE taught me that
  - ST-METANET, Pems-DRCNN, STGCN & Spacetimeformer performed similarly well.
  - PEMS bay train each model better than METR-LA
  - Each model did well for its architecture.
- The Spat. CEHE taught me that
  - AEs are better that GANs for smaller datasets
    - GANs are harder to train & require more data than AEs
  - Due to the much larger representation size (S:28224(36*28*28) vs T:1096) and milder gradient
    - Some spatial models can be better than some temporal ones, as they experienced much larger data
- Future plans & recommendations
  - More LSTM/AE/GAN variants
  - Prioritise Pre-MMS LSTM
  - Daily rasters
  - Do more subtests
    - Vary more HPs
    - broader HP-ranges
- The Temp. CEHE taught me that
  - As long as FBProphet is better, never trust the LSTM.
  - It's possible that a least LSTM will defeat FBProphet (if well tuned)
  - The more frequent a series, the better a model trains.
- The ST-METANET & Spacetimeformer
  - Have a RAM problem
- Finally, I've learned that
  - Newer, more complex models doesn't always outperform older, more simple ones
  - The subtests will eventually lead to
    - "HP-Tuning"

Findings of my Thesis & Discussion (2/2)

- Open questions
  - Is there any model that are good and dealing with CEHE dataset BOTH in spatial and temporal domain?
    - Currently no, because the datasets of most of the explored models involve sensors recording values at each timestamp
    - But my dataset has no sensors, only list of coordinates with only 1 frequency each. And thus, must be rasterized to predict/reconstruct heatmaps.
  - If you combine the best in temporal model and the best in spatial model for CEHE dataset, what would be the model looked like?
    - ~~VAE-FBP,~~ VAE-LSTM

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Discussion & Conclusion: What have I done?

- Technical basics
  - Applications, DL-Techniques
- Paper survey
  - SOTA models are compared in my ECE.
  - Common models are implemented to my fire event data
- Comparison tests
  - ECE
  - CEHE
    - How STDM works?
    - Rasterised Heatmap Generation
    - Time series prediction
    - HP subtests
- Discovered facts
  - (Newer, more complex vs older, more simple models)
  - [BEST ECE] DEEPFORECAST multi-LSTM
  - [BEST CEHE] VAE & FBProphet
- Discussion
  - Gave future subtest recomms.
  - Listed some open problems
  - Further discuss the results
  - Pointed out current issues
  - Indicated future research directions.

Question Time!

Q&As.